

# **Atmospheric Rivers (ARs):**

A Global Approach for our Regional Interest

Duane Waliser, Bin Guan, Mike DeFlorio, Vicky Espinoza
Jet Propulsion Laboratory/California Institute for Technology
Pasadena, CA

With significant collaboration / support from the Center for Western Weather and Water Extremes (M. Ralph et al.)

CA Department of Water Resources (J. Jones)

NASA Energy and Water Cycle Research Program (J. Entin)

#### **Metropolitan Water District**

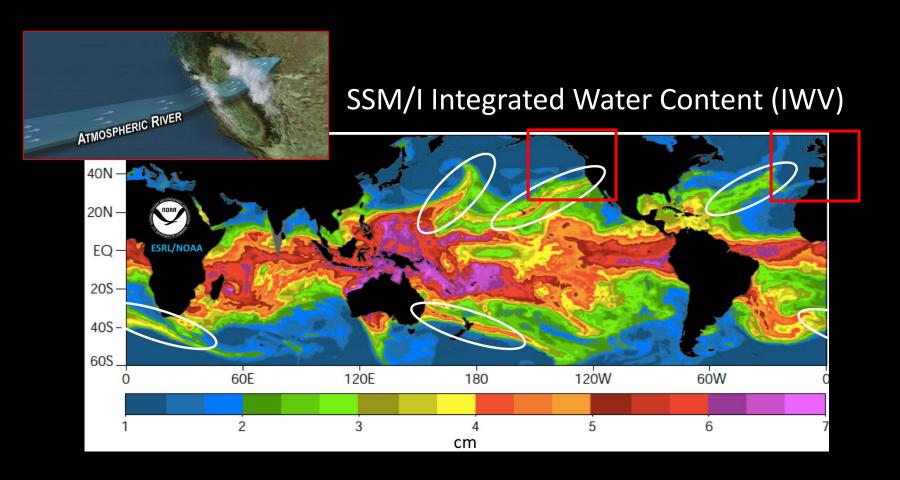
March 28, 2018

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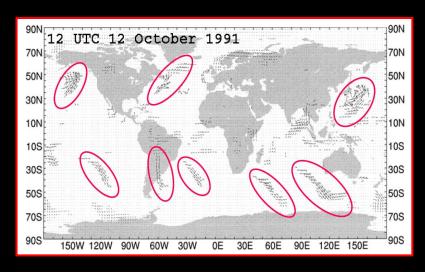
# Atmospheric Rivers (ARs)



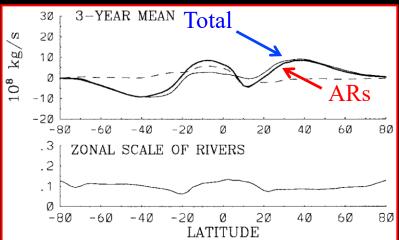
Most AR studies to date have been regionally focused on western N. America and western Europe.



# Origin of "Atmospheric Rivers"



Over 90% of poleward moisture transport at midlatitudes is by ARs that take up only ~10% of the zonal circumference; Zhu and Newell (1998)



These extreme storms influence global water and energy budgets, and thus shape Earth's climate.



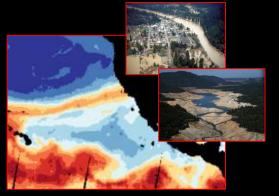
# AR Landfall Impacts

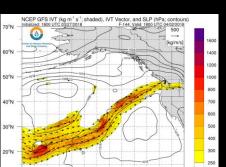


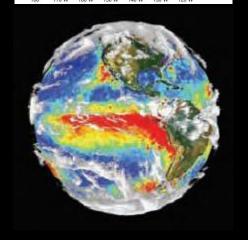
Account for ~40% of California's annual water supply in a few storms Account for most flooding events on U.S. West coast



## Regional Concerns vs Global Approach



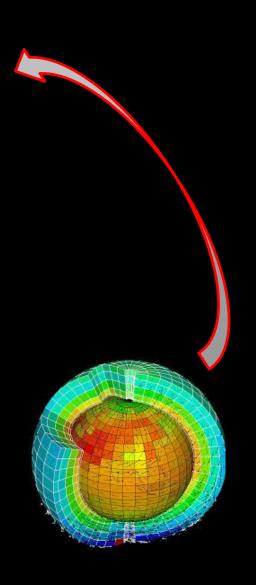




Manage California
Water Resources &
Flood Hazards

Management Aided by Accurate Weather & Climate Predictions

Modern Weather & Climate Prediction is a Global Consideration





### Outline

#### I. Global AR Considerations

- I. Detection
- II. Characteristics
- III. Impacts
- IV. Weather Predictions
- V. Climate Projections

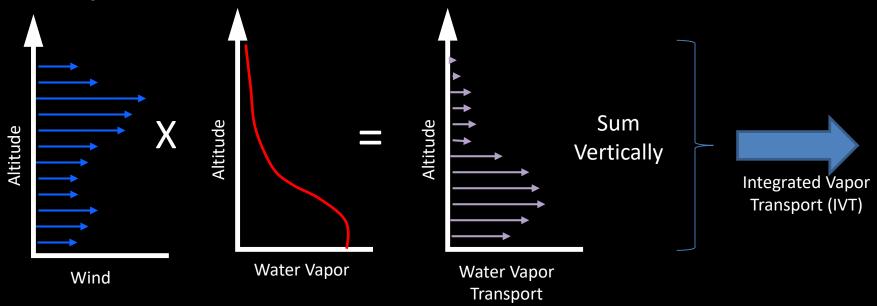
#### II. Regional AR Interests

I. Experimental Subseasonal (i.e. week 3) Predictions

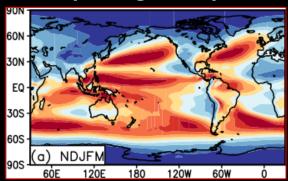


## Global AR Detection

#### I. Compute IVT

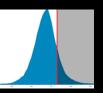


#### II. Map IVT globally



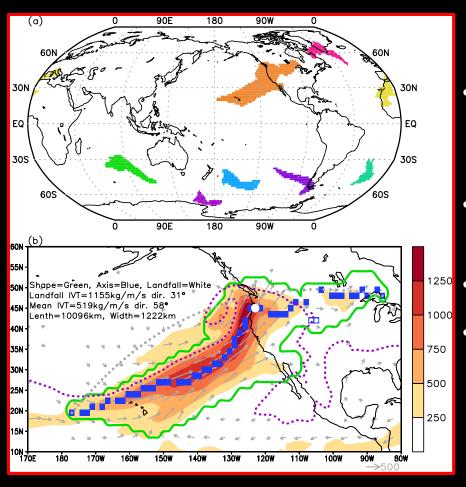
#### III. Apply AR Criteria

- IVT > 85th percentile
- Look for contiguous areas
- Length > 2000 km
- Length/Width > 2





## Global AR Detection

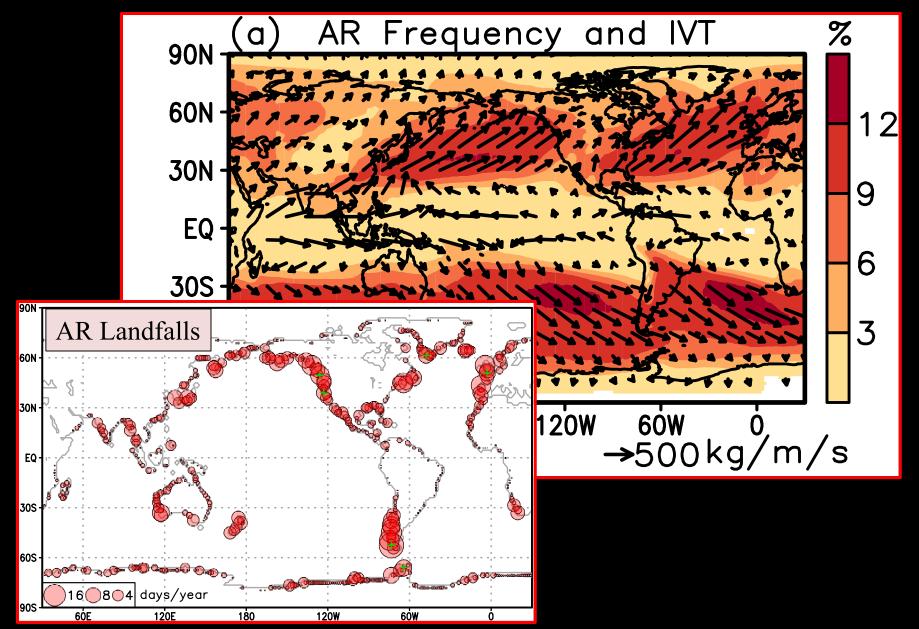


- AR detection applied to global "reanalysis" datasets (e.g., ERA-I, MERRA-2)
- ~30 year records, with AR maps every 6 hours
- Code and databases available.
- Developed for global studies analysis, modeling, prediction, etc.

Guan and Waliser (2015)



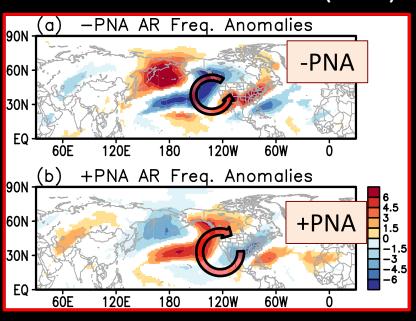
### **Global AR Characteristics**



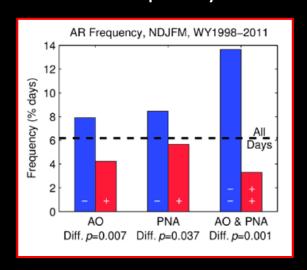


## Climate Patterns and ARs

#### Pacific-North American (PNA)



# Climate patterns, such as PNA, affect the frequency of ARs

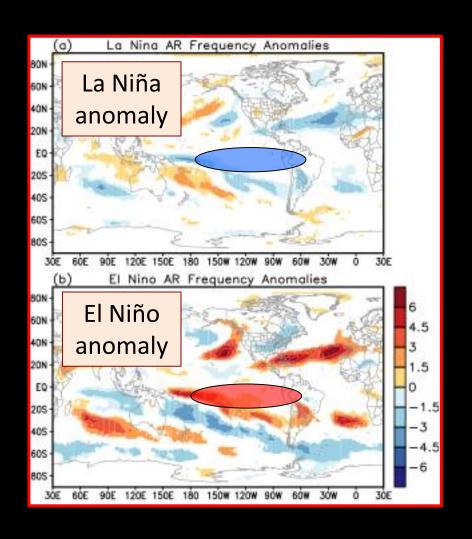


#### 2010/2011 Winter in California

- Largest total seasonal snow in previous 14 Years (~170% of normal)
- Largest # of AR days (twice normal)
- –PNA and –AO Conditions



## Climate Patterns and ARs



El Nino Southern Oscillation (ENSO)

Impacts AR Frequency
Across the Globe

Longer-lead predictions of ARs may be enabled by these slowly evolving "climate" patterns



## AR Extremes & Global Impacts

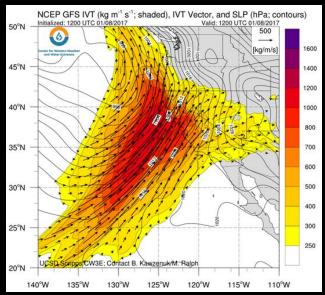


Image from M. Ralph/CW3E/SIO/UCSD

- A strong Atmospheric River (AR) made landfall over the U.S. West Coast on 8-9 January 2017.
- A number of locations experienced over 12 inches of precipitation over 3 days, and were exposed to extreme wind conditions.
- The extreme storm conditions resulted in the demise of the "Tunnel Tree", a giant sequoia in Calaveras Big Trees State Park, California

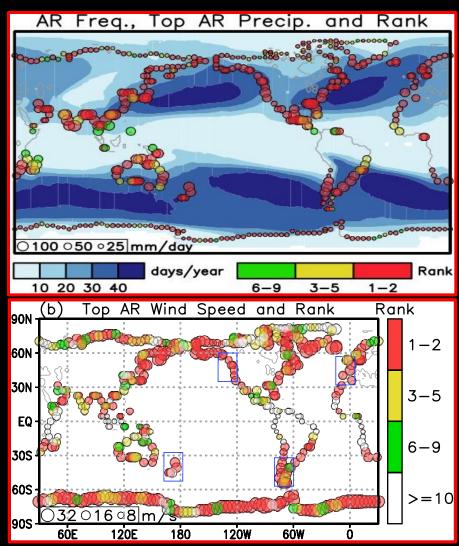




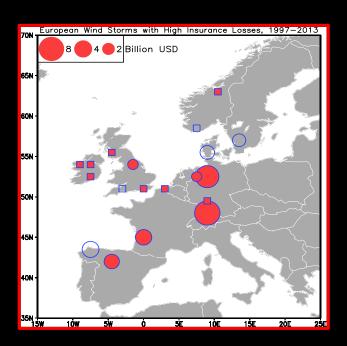
Pioneer Cabin Tree, also known as the "Tunnel Tree", a giant sequoia in Calaveras Big Trees State Park, CA



# AR Extremes & Global Impacts Wind & Precipitation



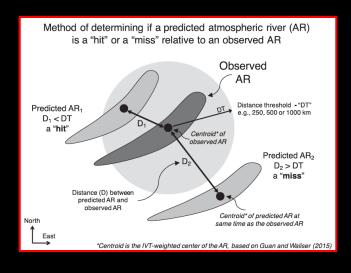
Circle color (size) indicates the rank (speed) of 10 m wind extremes that are connected to an AR considering all 6-hourly ECWMF surface wind values from 1997-2014.



Of 19 damaging wind storms with insurance losses in \$B US over Europe from 1997-2013, 14 (filled) were associated with ARs. Circle size indicates size of \$ loss; squares are less than \$1B.



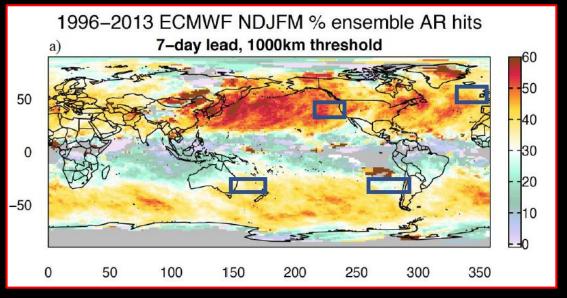
# Predicting AR Events



How well do our global NWP models – ECMWF in this case - predict AR occurrence & position?

ECMWF Subseasonal to Seasonal (S2S) hindcasts include twice-per-week, 11 member ensembles, from 1996-2013.

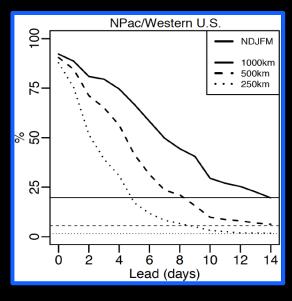
Courtesy WCRP/WWRP S2S Project



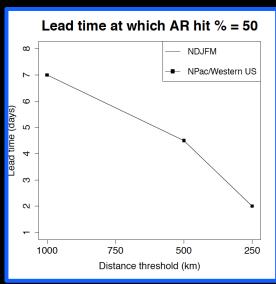
DeFlorio, Waliser, Guan, Lavers, Ralph, Vitart (2018)

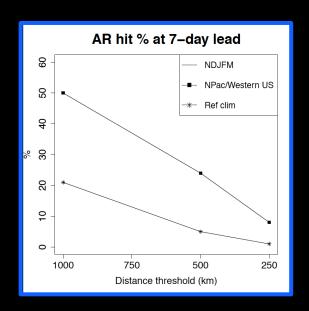


# Predicting AR Events



## Decision Support Tradeoffs



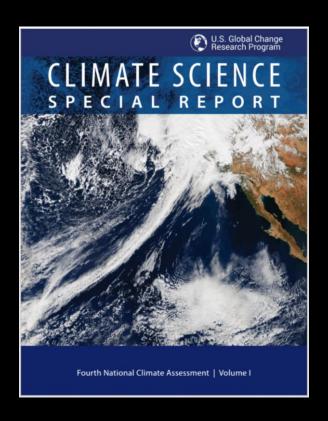


DeFlorio, Waliser, Guan, Lavers, Ralph, Vitart (2018)



#### **Previous Studies**

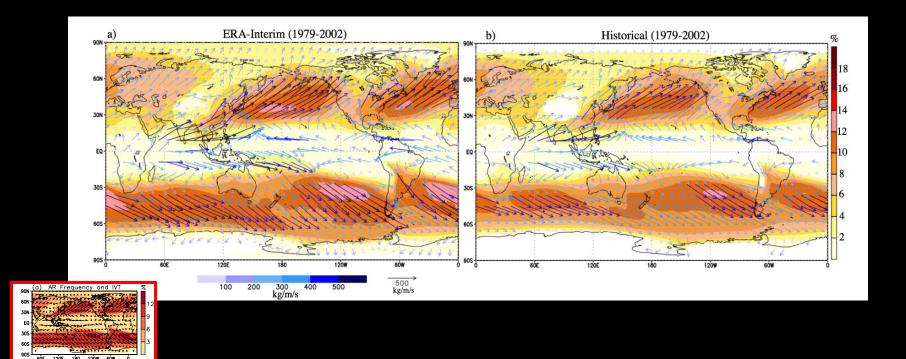
Publication	Historical Period	Projection Period	Geographic Region	AR Freq (± %)	AR IVT (± %)
Dettinger (2011)	1961- 2000	2046 - 2065; 2081 - 2100	CA Coast	+ 30	+ 10
Pierce et al. (2013)	1985 - 1994	2060s	CA Coast	+ 25 - 100	
Warner et al. (2015)	1970 – 1999	2070 - 2099	US West Coast	+ 230 - 290	+ 30
Payne and Magnusdottir (2015)	1980 - 2005	2070 -2100	US West Coast	+ 23 - 35	
Gao et al. (2015)	1975 - 2004	2070 - 2099	US West Coast	+ 50 - 600	
Hagos et al. (2016)	1920 - 2005	2006 - 2099	US West Coast	+ 35	
Shields et al. (2016)	1960 - 2005	2055 - 2100	US West Coast	+ 8	
Espinoza et al. (2018, current study)	1979 - 2002	2073 - 2096	US West Coast	+ 45	+ 30
Lavers et al. (2013)	1980 - 2005	2074 - 2099	W. Europe	+ 50 - 100	
Gao et al. (2016)	1975 - 2004	2070 - 2099	W. Europe	+ 127 - 275	+20 - 50
Ramos et al. (2016)	1980 - 2005	2074 - 2099	Europe	+100 - 300	+ 30
Shields et al. (2016)	1960 - 2005	2055 - 2100	North Atlantic	+ 4	
Espinoza et al. (2018, current study)	1979- 2002	2073-2096	W. Europe	+ 60	+ 30



- No Global Studies
- No way to compare UK & US, different models, methods and algorithms
- What about outside UK & US?

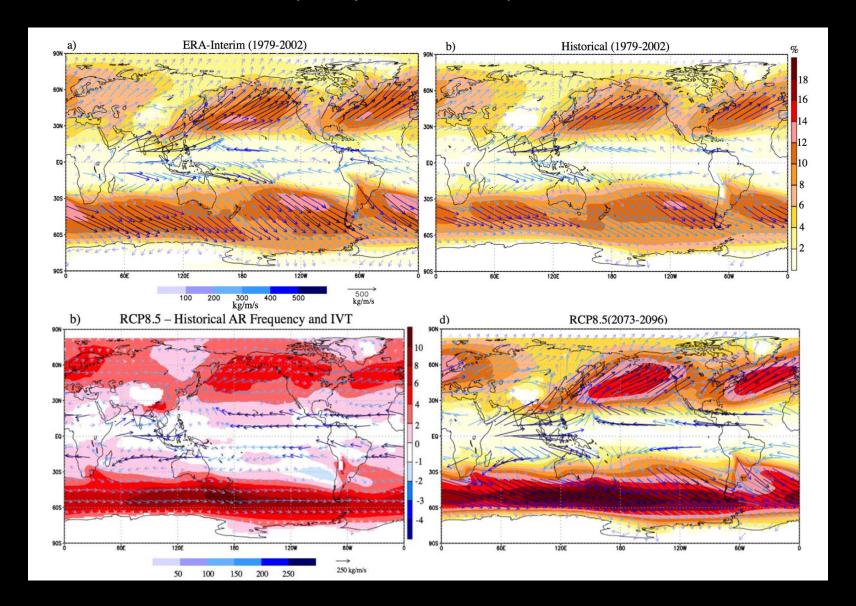


AR Frequency, Size & Transport: 21 CMIP5 Models





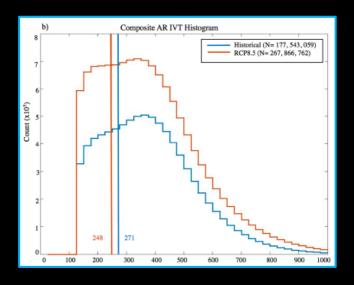
AR Frequency, Size & Transport: 21 CMIP5 Models



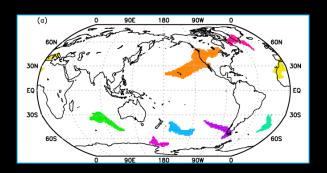
Espinoza, Waliser, Guan, Lavers, Ralph (2018, submitted w/ revisions)

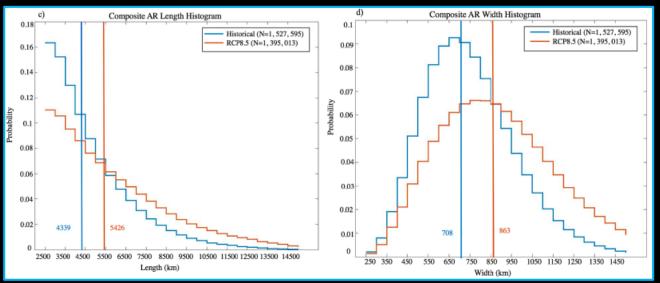


AR Frequency, Size & Transport: 21 CMIP5 Models



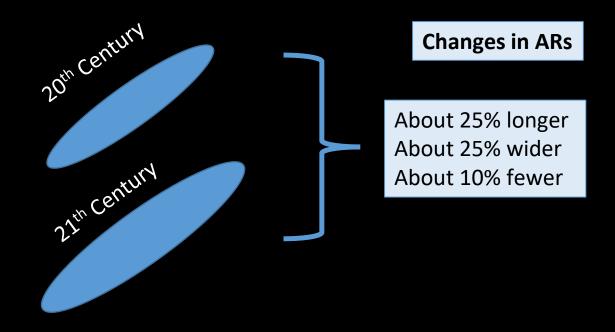
#### AR conditions vs AR Events





Espinoza, Waliser, Guan, Lavers, Ralph (2018, submitted w/revisions)





**AR Conditions = Number ARs \* Length \* Width** 

About 40% Increase in AR Conditions

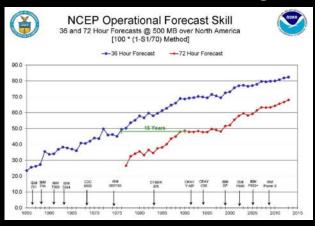
Occurrence of extreme IVT values within ARs ~double.



# Weather Forecasts O-14 Days

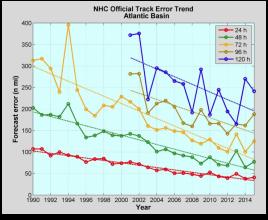


#### Forecast Skill Increasing



**General Weather Patterns** 

#### **Forecast Errors Diminishing**



Hurricanes

More/Better Observations
Improved Models
More Computing Power

... cold spells, hurricanes, heat waves, thunderstorms/tornados, nor'easters, santa ana winds, etc



# **Forecast Lead Times**

Weather 0-14 Days

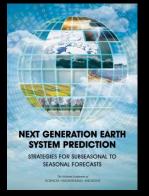
Subseasonal 2-12 Weeks

Seasonal 3-12 Months

Interannual 1 year - Decade

Climate Decades - Centuries

Subseasonal to Seasonal (S2S) 2 weeks -12 months

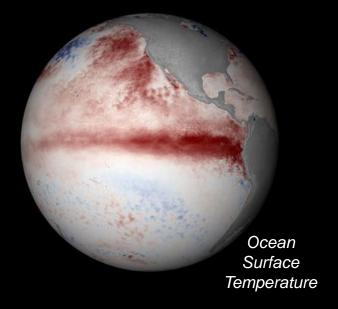


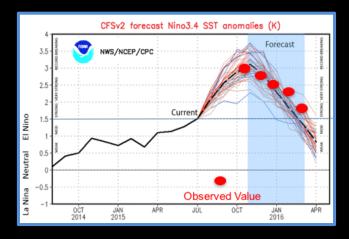
2016 NAS Report



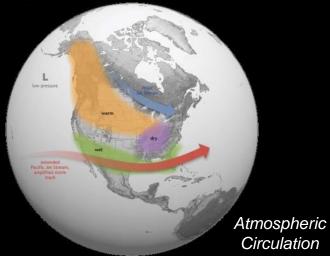
# s2S: El Nino – La Nina

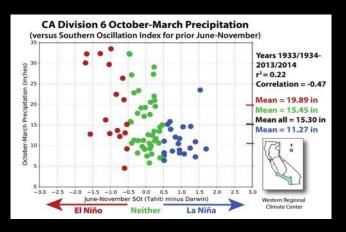
LifeCycle ~Months





Tropical SST – Capabilities to Predict



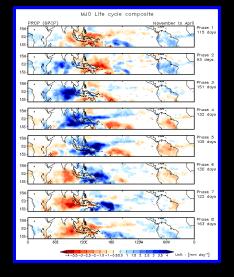


Extra-tropical Impacts – Difficult/Still Learning



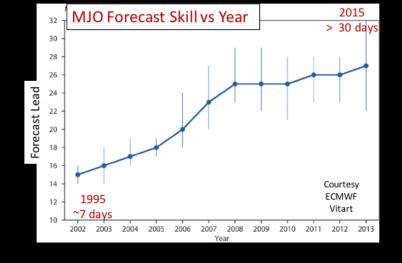
### S2S: Madden-Julian Oscillation

LifeCycle ~Weeks



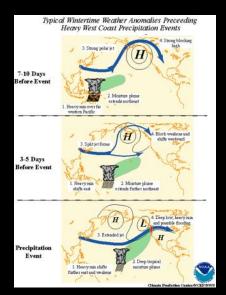
40-50 Days

Tropical Precipitation & Circulation



Tropical MJO – Skill out to 3-4 Weeks

Extra-tropical Impacts – Difficult/Still Learning



Extra-tropical Atmospheric Circulation More/Better Observations
Improved Models
More Computing Power



# Subseasonal AR Forecasts Experimental - Week 3

#### Experimental Atmospheric River Forecast\*

Issued on Monday, March 12, 2018

#### Contents:

**Slides 1 and 2:** "**Weather**" - Typical presentation of US west coast weather/precipitation forecast over lead times of 1 to 14 days considering only the likelihood of an atmospheric river (AR) occurring on a given forecast day. *Novelty – a weather forecast presented only in terms of AR likelihood.* 

Slides 3 and 4: "Subseasonal" - US west coast weather/precipitation forecast for week 3 considering the likelihood of an atmospheric river occurring in the given forecast week.

Novelty – as above, but also specifically for week 3, an extended/long-range or "subseasonal" prediction

\*This is an experimental activity for the 2017-18 and 2018-19 winters. Methodologies and hindcast skill are documented in DeFlorio et al. (2018a,b). Further validation of the real-time forecast results is required and underway. This phase of the research includes gathering stakeholder input on the presentation of information – feedback is welcome.

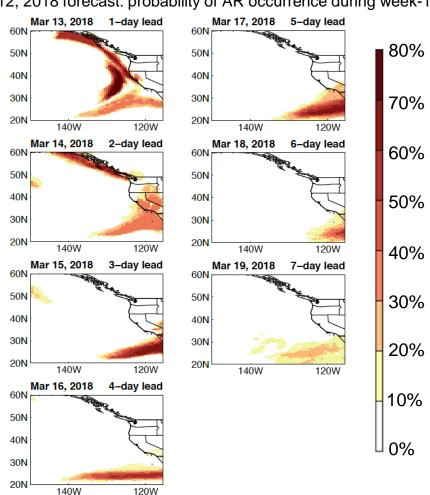
POC: Michael J. DeFlorio (michael.deflorio@jpl.nasa.gov)







March 12, 2018 forecast: probability of AR occurrence during week-1



# Week-1 (1-day to 7-day lead)

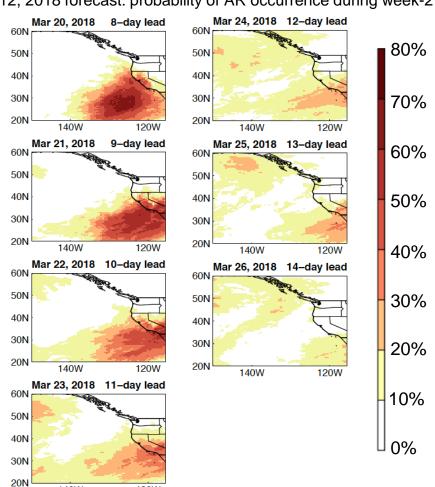
Experimental AR forecast issued on Monday, March
 12, 2018 by M. DeFlorio, A. Goodman, D. Waliser,
 B. Guan, A. Subramanian, and M. Ralph using 51-member real-time ECMWF data for an
 Experimental AR Forecasting Research Activity
 sponsored by California DWR





Contact: M. DeFlorio (michael.deflorio@jpl.nasa.gov)

March 12, 2018 forecast: probability of AR occurrence during week-2



140W

120W

# Week-2 (8-day to 14-day lead)

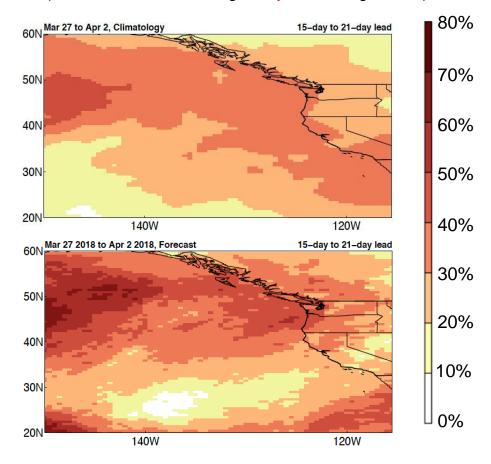
Experimental AR forecast issued on Monday, March
 12, 2018 by M. DeFlorio, A. Goodman, D. Waliser,
 B. Guan, A. Subramanian, and M. Ralph using 51-member real-time ECMWF data for an
 Experimental AR Forecasting Research Activity
 sponsored by California DWR





Contact: M. DeFlorio (michael.deflorio@jpl.nasa.gov)

March 12, 2018 forecast: probability of AR occurrence during week-3 (chance of an AR occurring at any time during week-3)



# Week-3 (Combined 15-day to 21-day lead)

Top row: hindcast climatology (ECMWF 1996-2015 data)
Bottom row: real-time forecast (ECMWF 51-member ensemble)

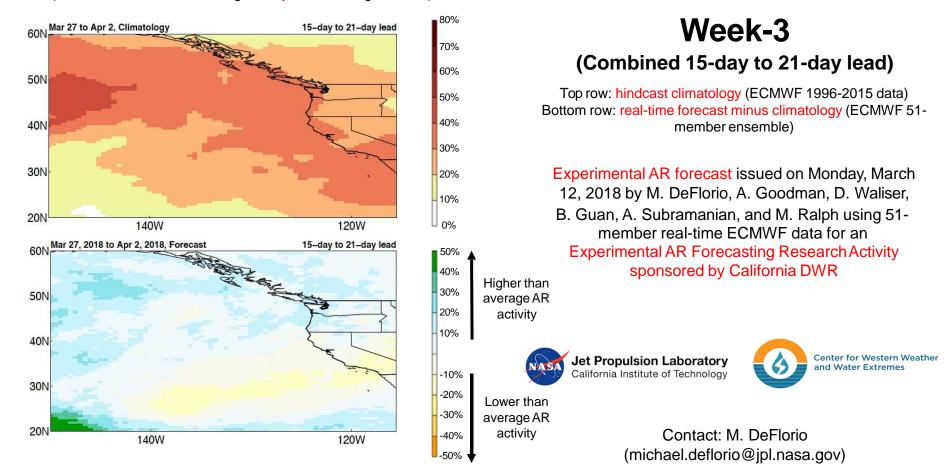
Experimental AR forecast issued on Monday, March
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 Experimental AR Forecasting Research Activity
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Contact: M. DeFlorio (michael.deflorio@jpl.nasa.gov)

March 12, 2018 forecast: probability of AR occurrence during week-3 (chance of an AR occurring at any time during week-3)





## Summary

- Atmospheric Rivers are a global phenomena that shape the Earth's climate, water and energy cycles, as well as account for regional weather and water extremes.
- We've developed a detection algorithm that can be *consistently* used on global "observations" (i.e. re-analyses), climate simulations and forecast models.
- Using this detection algorithm, we are developing model diagnostics and performance metrics, in conjunction with other observations (e.g. in-situ CalWater, satellite), to:
  - Identify and characterize hydrometeorological impacts from ARs
  - Evaluate model performance and identify weaknesses to guide model improvement.
  - Quantify forecast skill in a suite of operational S2S/weather prediction models.
  - Characterize projected 21<sup>ST</sup> century changes in Atmospheric Rivers.
  - Develop experimental week-3 AR activity forecast products.

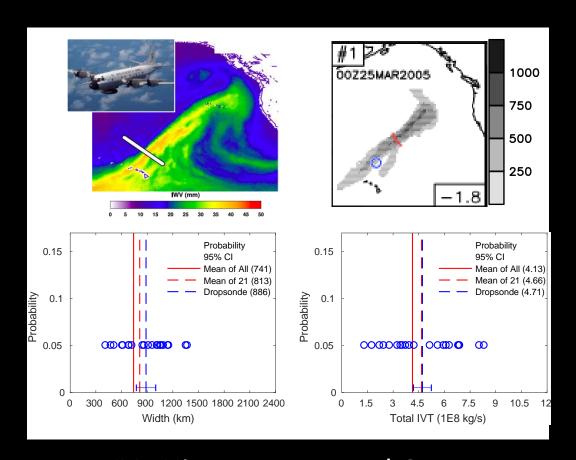
### **References Cited**

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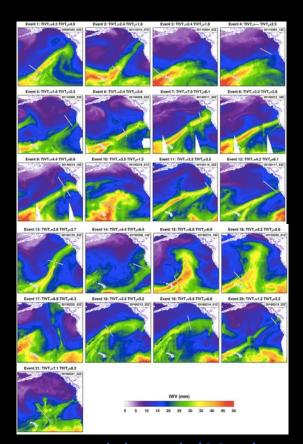
  An Inter-comparison Between Reanalysis and Dropsonde Observations, J. Hydromet, In Press
- Guan, B., D. E. Waliser, N. Molotch, E. Fetzer, and P. Neiman (2012), Does the Madden-Julian Oscillation Influence Wintertime Atmospheric Rivers and 1 Snowpack in the Sierra Nevada?, Monthly Weather Review, 140, 325-342.
- Ralph, F.M., S. F. Iacobellis, P. J. Neiman, J. M. Cordeira, J. R. Spackman, D. E. Waliser, G. A. Wick, A. B. White, and C. Fairall (2017), Dropsonde Observations of Water Vapor Transport within North Pacific Atmospheric Rivers, Journal of Hydrometeorology, Under revision.
- Waliser, D. E., and B. Guan (2017), Extreme winds and precipitation during landfall of atmospheric rivers, Nature Geosciences, DOI: 10.1038/NGEO2894.



# Algorithm Validation Support from CalWater Guan, Waliser and Ralph (2018)



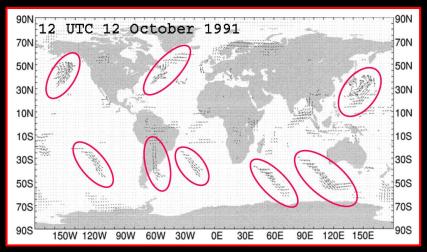
IVT Histograms Based On 5636 NE Pacific ARs from ERA-I 125-163W, 23-46N Jan 15-Mar 25 1979-2016

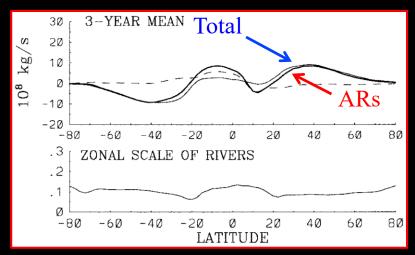


Ralph et al. (2017)
21 AR Event Transects
4.7 +/- 1.9kg/s
Min 1.3; Max 8.3



# AR History: Poleward Moisture Transports Influencing global Climate & Water Extremes





Over 90% of poleward moisture transport at midlatitudes is by ARs that take up only ~10% of the zonal circumference; Zhu and Newell (1998)

For discussion on connections between ARs, Tropical Moisture Exports (TMEs) and Warm Conveyor Belts (WCBs), see Cordeira (2015).

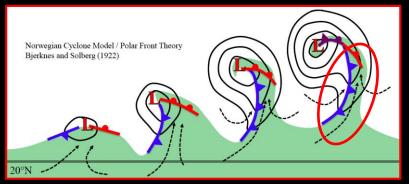


Figure courtesy J. Cordeira, Plymouth University

See AMS Glossary